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Power Systems 2.0: Designing an Energy Information System for Microgrid Operation

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Completed Research Paper

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Abstract

In this paper we demonstrate the contribution of information systems towards a sustainable and reliable power supply. Following a Design Science approach we develop an information system for microgrid operation at a U.S. army base. Microgrids enable an improved integration of distributed renewable energy sources and increase the robustness of the overall power grid. The microgrid in this study contains extensive photovoltaic generation, the energy demand of the base, as well as energy storage. The information system we design controls and optimizes microgrid operations under uncertainty, as well as physical and organizational constraints. Using real-world data to evaluate the system, we show that it substantially increases the amount of clean photovoltaic energy that can be generated while simultaneously decreasing energy costs of the base. Thereby, we are able to improve the ecological and economic efficiency of the microgrid.

Keywords: Design Science, Environmental sustainability, Energy Informatics, Case study/studies

Introduction

As part of the discussion on how information systems can help society shape a more prosperous future and a sustainable way of living, the concept of *Energy Informatics* (EI) has received widespread attention in recent years (Goebel et al., 2014). A core concern of EI research has been the changing shape of the power grid, with *information and communication technology* (ICT) complementing traditional power systems. An emphatic push of societies around the globe away from fossil fuels towards renewable energy sources holds the promise of a cleaner energy supply, but also comes with new challenges that need to be overcome. Decentralized energy generators, such as photovoltaic panels or *combined heat and power* (CHP) units, pose challenges to grid operators and the traditional grid structure (Paatero and Lund, 2007). Similarly, the volatility of some renewable energy sources in general require novel demand side management measures that employ ICT infrastructure to align supply and demand in the grid (Strüker and van Dinther, 2012).

In this paper we present a case study that analyzes how *microgrids* can alleviate these issues and the substantial contribution IS research can make towards the implementation of microgrid concepts. Microgrids are localized electricity distribution systems that operate in a controlled, coordinated way, either while connected to the main power network or while islanded (Lasseter and Paigi, 2004). Essentially, microgrids attempt to balance supply and demand on a localized level, thereby reducing the volatility of the overall system. In addition to an improved integration of renewable energy sources, they also provide a more resilient power infrastructure in the face of disaster (Kwasinski et al., 2012) and new opportunities for establishing rural electrification in third-world countries (Chaurey and Kandpal, 2010; Nandi and Ghosh, 2009). The concept of microgrids has been researched for several years with respect to their physical foundations, as well as their theoretical economic feasibility, which have been investigated quite thoroughly. The role of IS research becomes evident when considering the implementation of a microgrid and the associated cost-efficient management of supply and demand, given fluctuating loads and generation, flexible energy tariffs, as well as organizational constraints.

The case study discussed in this research concerns a microgrid to be implemented at a U.S. army base. The base contains a 2 megawatts photovoltaic (PV) installation (which is to be increased by an additional megawatt). Since only a maximum of 1 megawatt of power may be exported at any time, parts of the PV installation frequently need to be disconnected from the grid, essentially wasting energy that could have been generated. As this contradicts the government's stated environmental goals, a 1 megawatt-hour battery has also been installed. Adhering to the design science research paradigm (e.g. Hevner et al., 2004), we design an IS artifact that determines operational decisions for the microgrid given the mentioned, as well as other physical, economic, and organizational restrictions. Specifically, we address the following research questions:

RQ1: What requirements does the information system need to satisfy (*Requirements Analysis*)

RQ2: How does the corresponding information system need to be designed (*Artifact Design*)

RQ3: Are the initial requirements satisfied and what is estimated benefit of the IS-enhanced microgrid? (*Evaluation*)

While the IS artifact consists of several modules, the optimization module employs DER-CAM, a well-known optimization tool for microgrid operation developed at Berkeley National Laboratory. DER-CAM will be introduced in more detail in the following section, along with related work from within the IS community, as well as other disciplines that have conducted microgrid research. The third section provides an overview of the research design of the entire microgrid project and defines the scope of this study in its context. The requirements analysis (RQ1) is also addressed in this section. The subsequent section contains the actual design process and the evaluation of the resulting artifact (RQ2 and RQ3), followed by a section discussing the implications of our work. We conclude by summarizing this study and pointing out possible paths for future research.

Relevance to IS Research and Related Work

The research questions that are raised in this study address the issue of how information systems can increase the effectiveness and efficiency of modern power systems, particularly in the context of renewable

energy. It thereby directly relates to the goals of eco-effectiveness and eco-efficiency postulated in Watson et al. (2010) as central objectives of Energy Informatics research. Therefore, Energy Informatics and the related concept of *Green IS* provide the theoretical anchor for our research within the IS community. The first part of this section is subsequently dedicated to works that relate to our approach in these fields of IS research. The second part addresses research on microgrids outside the IS discipline and elaborates on DER-CAM, the optimization module of our IS artifact.

Green IS and Energy Informatics

Green IS, as a subfield of Information Systems research, concerns the role of information systems in enabling, enhancing, and encouraging environmentally sustainable behavior and processes. While there has been pioneering research on these topics for several years, IS research on environmental sustainability gained particular traction within the community at the beginning of the current decade, with several publication in high-profile outlets emphasizing the importance of Green IS research, providing theoretical groundwork, and proposing research agendas (e.g. Melville, 2010; Watson et al., 2010; Elliot, 2011). Since then, various journal publications have further helped to position the discipline (e.g. vom Brocke et al., 2013; Malhotra et al., 2013) and to present promising Green IS applications (Seidel et al., 2013; Loock et al., 2013). This is complemented by a vast amount of conference publications, with Green IS research regularly featuring at all major IS conferences.

Our research project is a genuine application of Energy Informatics research, as outlined in Watson et al. (2010). In their Energy Informatics Framework, they position the information systems at the confluence of *flow networks* (circuits, power grids, pipelines, etc.), *sensor networks* (that report data on the flow network and environmental factors, such as a smart meter), and *sensitized objects* (that report data on their use and may be remotely controllable). Figure 1 illustrates how the setting of the microgrid project reflects this framework. A difference to the original framework, as in Watson et al. (2010), is that sensitized objects in a microgrid are not limited to the demand side, since the PV panels can be remotely disconnected and the very purpose of the battery is the flexibility between supply and demand. The framework puts this setting in the context of eco-goals, which we have previously discussed, and the stakeholders. The interests of the stakeholders are particularly significant in this project, since they define both objective and constraints of the system. The U.S. government as operator of the base naturally seeks to reduce necessary operational spending. However, the public perception of “green” public buildings is similarly significant to an administration that puts an increasing emphasis on sustainability. The utility company defines the energy tariff on the one hand, and constrains the maximum energy that can be exported by the base on the other.

Naturally, there has been some research directly related to our approach within the Energy Informatics community in recent years. For instance, Feuerriegel et al. (2012) and Bodenbenner et al. (2013) analyze

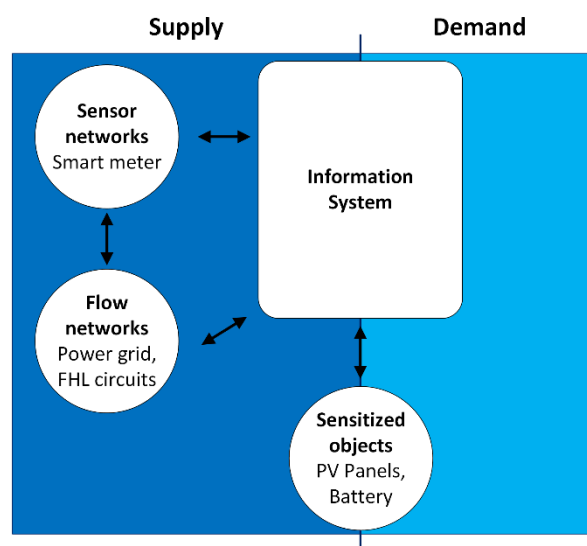


Figure 1. The microgrid setting in the Energy Informatics Framework, based on Watson et al. (2010)

how IS design can contribute to the realization of demand response systems. These systems allow demand to be curtailed at certain times (*peak-clipping*) or moved to different times (*load-shifting*), thereby aligning it with energy supply. Brandt et al. (2013) introduce an information system that analyzes driving behavior to determine charging and discharging times for the battery of an electric vehicle. While our microgrid does not include electric vehicles, the battery installed at the base can provide additional supply or demand of energy on a flexible basis. These studies exemplify the contribution IS design can make to smart energy systems by providing coordination in the face of uncertainty and under organizational constraints.

General Research on Microgrids

Research on microgrids has been conducted for more than a decade (e.g. Lasseter and Paigi, 2004; Venkataramanan and Illindala, 2002). They are generally considered to be a solution to the problems and opportunities arising from the increasing decentralization of the power system due to renewable energy sources and distributed generation (Lasseter et al., 2002). During this time, two main research streams concerning microgrids have emerged. The first investigates control and coordination mechanisms for microgrids. For instance, Dimeas and Hatziaargyriou (2005) present a multi-agent system for microgrid control, while Katiraei and Iravani (2006) analyze reactive strategies for power management. Publications in this context are either on a theoretical or conceptual basis. The second research stream investigates actual microgrid implementations. Examples include Nandi and Ghosh (2009), who evaluate a wind and battery based microgrid in Bangladesh, and Marnay et al. (2011), who discuss the microgrid at the Santa Rita Jail, a “green prison” in California. These implementations usually use very simple control strategies for the microgrid that do not exploit its full potential.

This divergence between highly sophisticated control mechanisms that have been developed on a theoretical level and the simple management strategies that are actually implemented is due to the need for information of a certain quality to realize the former. For instance, the optimization of microgrid operations over a span of 48 hours requires reasonably reliable information on demand and energy generation within the microgrid. The design of such an information system that enables microgrid optimization under uncertainty is the research gap we address in this paper. As the actual optimization module within the information system we employ DER-CAM (*Distributed Energy Resources Customer Adoption Model*). DER-CAM was originally designed as a tool to determine the optimal investment decisions for distributed energy resources, such as solar power, combined-heat-and-power systems, or batteries, in microgrids as well as for individual buildings. It is based on the General Algebraic Modeling System (GAMS). A new version of DER-CAM is also able to optimize microgrid operation over a certain time span (between 24 hours and one week), given information on future demand, generation, and prices. In this paper we develop an information system that provides forecasts of these factors. It furthermore handles the resulting decisions of DER-CAM at each time step, given forecast uncertainty and physical as well as organizational constraints. To our knowledge this is the first time that microgrid implementations are considered from an IS perspective and that an actual microgrid implementation is investigated with respect to operational optimization under uncertainty.

Problem Statement and Research Design

This study is part of a project that establishes a microgrid at a U.S. army base. The occupancy of the base changes periodically between the permanent staff of about 250 residents and several thousand due to training schedules. The electrical network of the base is outlined in Figure 2. Originally equipped with a 1 megawatt-peak (MWp) photovoltaic installation, another megawatt was added in late 2013, with a third currently being installed. Since the goal is to have a zero net-energy base, the solar installation will eventually reach 8 MWp. To stabilize grid operations, the utility company limits the possible export of PV power through the coupling point to one megawatt. If this amount is exceeded, parts of the PV installation would need to be disconnected, which can only be achieved in 0.5 MWp-segments. This is inefficient both from an ecological and economic perspective. Curtailing PV generation decreases the amount of clean energy produced by these installations. This energy also comes at virtually zero marginal cost, which enforces the economic argument. Since the power demand of the base usually varies between 0.8 and 1.8 MW, the threshold is regularly exceeded even by a 3 MWp installation and poses a major problem for any increase in installed power. Hence, a 1 MWh Lithium-ion battery was installed to serve as a buffer for excess energy.

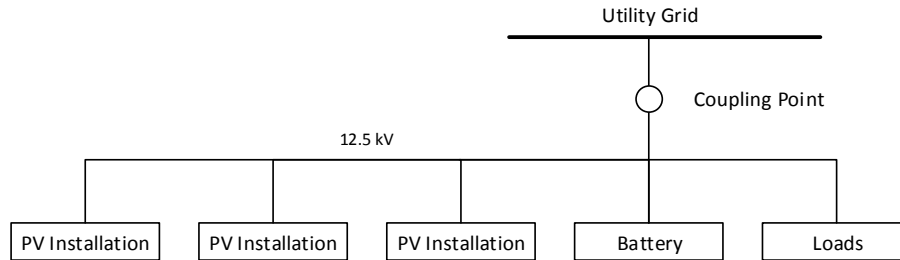


Figure 2. Electrical network at the test site

However, this battery can also be used for general demand shifts. The energy costs of the base are calculated according to the PG & E E-20 tariff structure (Pacific Gas and Electric Company, 2010), which designates different time-of-use rates for peak, part-peak and off-peak periods. More importantly, it also includes a demand charge for the highest peak, off-peak, and overall demand within a month, respectively. These demand charges account for a substantial share of total energy costs. Thus, it becomes evident that the management of the battery cannot be reduced to simple decisions, such as “charge if there is excess PV generation” or “discharge if loads exceed PV generation”. Instead, an accurate anticipation of future demand and generation, as well as an optimization according to these forecasts, are required to reduce the demand charges. The implementation of an information system that achieves all of these objectives is the general goal of the microgrid project.

The scope of this study within the project is illustrated in Figure 3 and includes the design and evaluation of a prototype of the information system to determine its expected impacts before it is eventually implemented. Since our research is design-oriented, we follow the guidelines for design science research as outlined by Hevner et al. (2004). The *relevance of our problem* has been established in the preceding sections. We develop a tool that improves the integration of renewable energy sources into our power systems and increases the stability of the overall system. We *design as an artifact* – the IT artifact produced by our research is the resulting software package that addresses the aforementioned goals. Our *research contribution* is, therefore, the development of this novel application of IS design to support environmental sustainability, which will be *evaluated* later in this paper.

Our actual design process relates to a software engineering approach. First, we analyze the requirements our information system needs to fulfill. Second, we design the information system. Third, we evaluate the components of the IS design where necessary, and fourth, we evaluate the overall system and test if the initial requirements are satisfied. Given the intended objective of our information system, we derive the following requirements. The first three requirements follow from the agenda of the U.S. government as primary stakeholder, which have been discussed in the previous section. The fourth requirement follows from the physical setting of the project and the agenda of the utility company.

- Requirement 1: *Ecological efficiency.* The primary goal of the project is to promote zero-net-energy consumption in government buildings. Hence, the information system must substantially reduce incidents when PV panels need to be shut off due to excess generation.
- Requirement 2: *Economic efficiency.* While ecological efficiency is the primary objective, the information system also needs to reduce operational costs of the microgrid compared to simpler battery management strategies.
- Requirement 3: *Forecast accuracy.* Since optimization occurs over a future timespan, the information systems must include components that supply the optimization module with forecasts of future demand and generation. These forecasts must be

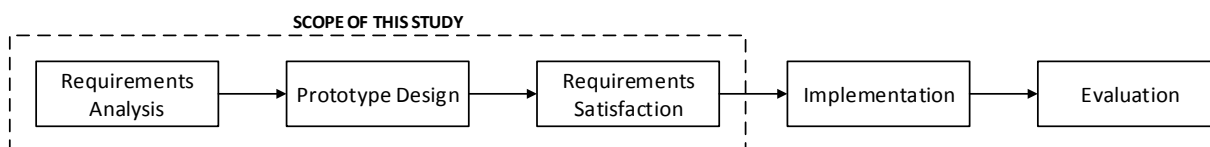


Figure 3. Research design of the Microgrid Project

reliable enough, so that optimization under uncertainty outperforms simpler strategies for battery management.

Requirement 4: *Observance of constraints.* The information system must account for organizational and physical constraints. These include contractual limits on exportable power, the fact that PV installations can only be disconnected discretely (500 kW segments), and the limits to the charging behavior of the battery.

In the following section we will present and evaluate the information system designed with these requirements in mind.

Information System Design and Evaluation

The information system we developed for the microgrid is illustrated in Figure 4. The IT artifact at its core contains five components: two forecasting modules, one for the load of the base and one for the photovoltaic generation; the optimization module running DER-CAM; a database for historical data on generation, weather, and load; as well as a supervising module. The purpose of the latter is for the coordination of the other modules and for communication with the components outside the artifact. The supervising module is written in Python and provides a link between the SQL-database, the GAMS-based optimization module, and the forecasting modules, which are currently running in R (although they will be moved to Python, as well, for the actual implementation). The inputs from the smart meters and the weather forecast are collected by an energy management software (EMS) that also controls the battery and can (dis)connect PV installations. Our IT artifact receives the metering and weather data and enacts the schedules determined by the optimization module through an interface with this software.

The implementation of the information system results in the following processes. At fixed intervals, the EMS triggers the supervising module through the interface for an updated schedule. The supervising module requests the current weather forecast and metering data. These are collected by the EMS and forwarded to the supervising module. The supervising module stores this new data in the database and retrieves and forwards historical datasets as required by the forecasters. The forecasting modules subsequently return the load and generation forecasts for the following 48 hours. The supervising module submits these values to the optimization module, which returns the optimal schedule given the forecasts. This schedule is eventually returned to and implemented by the EMS.

In the remainder of this section, we will first explain the methods behind the forecasting modules and the optimization module. Afterwards, we describe the setting used for the evaluation of the IT artifact. This is followed by the results, which include an evaluation of the forecasting components, as well as the overall system under different conditions.

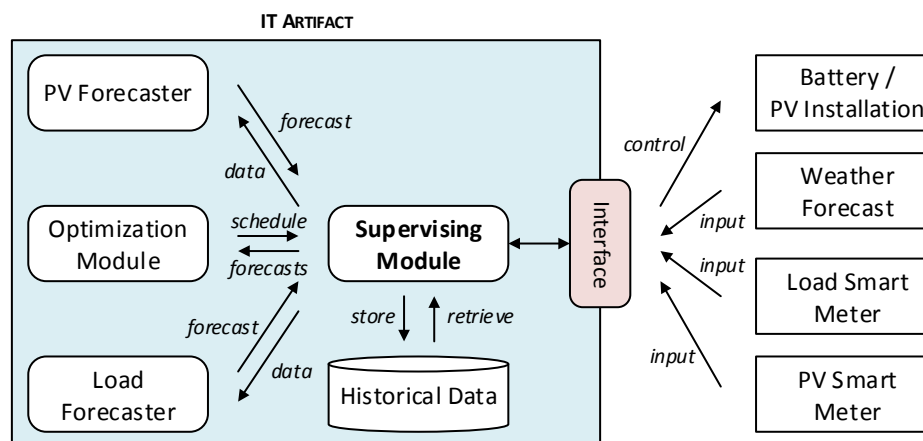


Figure 4. Schematic representation of the information system

Forecasting Modules

The **load forecaster** is based on the Discrete Fourier Transformation, since the load curve shows very reliable patterns on a day-of-week basis. Building upon work by Hedwig et al. (2010), who use a Fast Fourier Transformation (FFT) to forecast Wikipedia workload, which exhibits similarly stable patterns, we employ a FFT-algorithm (from the *stats*-package in R) to forecast the energy load for the army base. This is illustrated in Figure 5a and b. Figure 5a shows the demand curves for three successive Thursdays (blue) and the dominant frequencies that have been extracted by the FFT-algorithm (red). Figure 5b visualizes the fit between forecast (red) and actual load (blue) for the following Thursday.

While the fit is sufficiently good to serve as input for the optimizer, we mentioned the issue that the occupancy of the base sometimes changes substantially for several weeks at a time. While it would theoretically be possible to have an employee at the base provide information on the occupancy to the system, this presents several organizational challenges. On the one hand, it requires work hours that cannot be spent on other issues. On the other hand, occupancy of the base does not consistently translate to a certain increase or decrease of load, since it fundamentally depends on the activities of the occupants (e.g. computer-related vs. outdoor training). There is also the issue that a more detailed description of the occupants and their activities might touch sensitive information that does not need to be revealed to a microgrid operations information system. To overcome this problem, we introduce a learning parameter into the workload forecaster. Whenever deviations between forecast and actual load exceed a certain threshold for several successive periods, the part of the training dataset before these deviations started is scaled by a fraction of the average deviation in percent. This decreases the immediate forecasting error if base occupancy has changed, while limiting the impact of random deviations that are not related to an occupancy change (false positives).

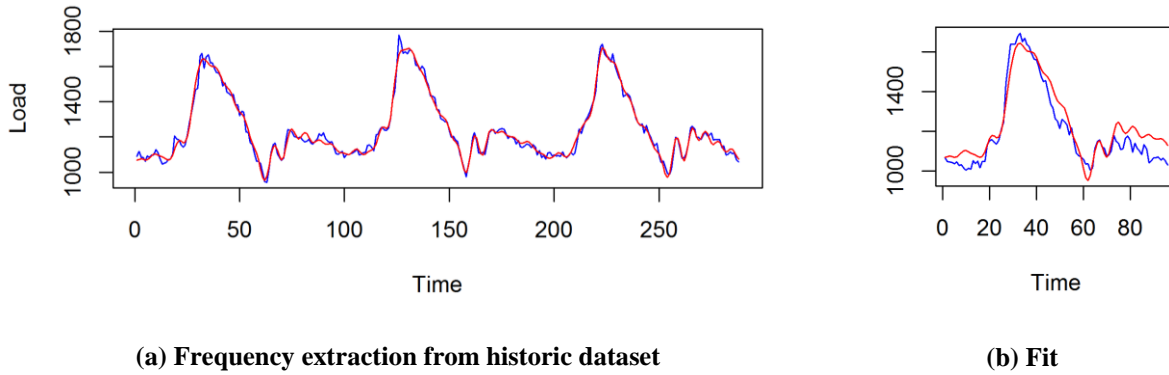


Figure 5. FFT-based Load Forecaster

The central assumption of our **forecasting module for the PV generation** is that power generated at time t , P_t^{PV} , on a clear day is directly related to the altitude of the sun above the horizon at that time, β_t (for $\beta_t > 0$). In the short term, this assumption is reasonable to provide a decent approximation, given the standard model by Masters (2004). He calculates the radiation on a PV collector that tracks the movement of the sun as

$$P_t^{PV} \sim I_t = A_t e^{-\frac{k_t}{\sin \beta_t}} \left[1 + C_t \left(\frac{1 + \sin \beta_t}{2} \right) + \rho_t (\sin \beta_t + C_t) \left(\frac{1 + \sin \beta_t}{2} \right) \right] \quad (1)$$

with ρ as the ground reflectance and A , k and C as the apparent extraterrestrial flux, the optical depth, and the sky diffuse factor, respectively. The latter three are seasonal variables that change slightly over the course of the year, but are basically constant in the short run. In fact, they change by substantially less than one percent between two successive days. However, the empirical data available for them is averaged over the continental United States and each month. Hence, the applicability of the values to our problem is dubious and it is infeasible to collect them manually.

To solve this problem, we transform and simplify the model such that it can be estimated by a linear regression – including the seasonal variables, which are assumed to be constant factors in the short term.

The terms in the brackets of Equation 1 represent the multipliers for the direct, diffuse, and reflected radiation, respectively. Direct radiation usually accounts for 80 to 90 percent of the total (Masters, 2004), hence we ignore the diffuse and reflected parts for approximation, which reduces the model for short-term considerations to

$$P_t^{PV} \sim A e^{-\frac{k}{\sin \beta_t}} \quad (2)$$

Taking the logarithm of both sides yields

$$\ln P_t^{PV} \sim \ln A - k \frac{1}{\sin \beta_t} \quad (3)$$

Hence, the relationship can be estimated through the linear regression

$$y_t = \ln P_t^{PV} = \alpha_0 + \alpha_1 \frac{1}{\sin \beta_t} \quad (4)$$

Since our assumptions only hold in the short term, the training sample for our regression contains data of the thirty most recent clear-sky daylight ($\beta_t > 0.05$) hours. If the interval to be forecasted contains points with cloudy or hazy weather, the clear-sky prediction is multiplied by a certain factor, depending on whether the forecasted weather is overcast (including rain / snow), partially clouded, or foggy. Since a qualitative phrase like “overcast” covers a relatively large spectrum of conditions, these factors are adjusted dynamically if deviations, i.e. $[E(P_t^{PV}) - P_t^{PV}]/P_t^{PV}$, exceed a certain threshold.

One issue that could potentially affect the precision of this forecasting model is the fact that it forecasts the logarithm of expected PV generation, which would need to be inverted to receive the expected PV generation the optimizer can work with. Since the linear regression weights a deviation between $y_t = 0.2$ and $E(y_t) = 0.3$ the same as the deviation between $y_t = 6.0$ and $E(y_t) = 6.1$, the model could result in substantial estimation errors in the upper ranges. To solve this, we approximate a second model that relates P_t^{PV} linearly to $\sin \beta_t$ (the derivation of this model is attached in Appendix A). While the first model better describes the functional form, the approximation in the second model reduces the impact of forecasting errors.

PV Model 1:

$$E(\ln P_t^{PV}) = \alpha_0 + \alpha_1 \frac{1}{\sin \beta_t}$$

PV Model 2:

$$E(P_t^{PV}) = \alpha_0 + \alpha_1 \sin \beta_t$$

Both models will be assessed during the evaluation later in this section.

Optimization Module

The optimization module uses the CPLEX-solver in GAMS to solve the following minimization problem. The variables and parameters are described in Table 1.

Equation 5 states the loss-minimizing objective function. The loss is defined as the sum of all demand charges and the energy costs over two days, measured in 15-minute intervals (for a total of 192 periods). The tariff follows net metering, i.e. energy is sold to the utility at the same price that it is purchased from the utility.

$$L = \min_{\vec{b}, \vec{z}} \left[c_1 \cdot M^{peak} + c_2 \cdot M^{part} + c_3 \cdot M^{total} + \sum_{t=1}^{192} p_t \cdot E_t \right] \quad (5)$$

The energy balance with the utility is the difference between load and photovoltaic generation plus any change in the amount of energy stored in the battery. Depending on whether the change is negative or positive, it has to be multiplied by the charging efficiency or its inverse, respectively (Equations 6 and 7).

$$\text{s.t.} \quad E_t = L_t - PV_t + \gamma_t b_t \quad \forall t \quad (6)$$

$$\gamma_t = \begin{cases} 1/\omega & \text{if } b_t \geq 0 \\ \omega & \text{otherwise} \end{cases} \quad \forall t \quad (7)$$

Table 1. Variables and parameters in optimization problem

$\vec{b} = (b_1 \ b_2 \ \dots \ b_{192})$	kWh	Vector that includes the change in the amount of energy stored in the battery for each period t
$\vec{z} = (z_1 \ z_2 \ \dots \ z_{192})$	None	Vector that includes the Photovoltaic segments that are disconnected in each period t
E_t	kWh	Energy balance with utility grid in period t (negative numbers imply that energy was sold to the utility)
p_t	USD / kWh	Price of energy in period t (defined through contract with utility)
$M^{peak}, M^{part}, M^{total}$	kW	Maximum demand during peak hours, part-peak hours, or any hours, respectively
c_1, c_2, c_3	USD / kW	Demand charge for maximum demand during peak hours, part-peak hours, or any hours, respectively
L_t, PV_t	kWh	Load and photovoltaic generation in period t
B_t	kWh	Energy stored in the battery at the beginning of period t
B^{min}, B^{max}	kWh	Maximum and minimum amounts of energy that can be stored in the battery, respectively
b^{dc}, b^c	kW	Maximum discharging and charging power of battery
ω	None	Charging and discharging efficiency (assumed to be equal)
PV_t^{eff}	kW / kWp	Photovoltaic efficiency in period t , i.e. power generated per power installed
PV^{inst}	kWp	Installed photovoltaic power
s_t, r_t	None	Booleans, equal to 1 if t is a peak period or part-peak period, respectively

The amount of energy stored in the battery in $t + 1$ is the amount stored in t plus the change b_t (Equation 8). B_1 , i.e. the energy at the beginning of the optimization, is provided by the supervising module.

$$B_{t+1} = B_t + b_t \quad \forall t \quad (8)$$

Equations (9) and (10) define limits to the amount of energy that can be stored in the battery and to the change of that amount within a single period.

$$B^{min} \leq B_{t+1} \leq B^{max} \quad \forall t \quad (9)$$

$$b_t \in \{\mathbb{R} \mid b^{dc} \cdot 0.25 \leq b_t \leq b^c \cdot 0.25 \cdot \omega\} \quad \forall t \quad (10)$$

The maximum power export is 1000 kW, equal to 250 kWh in a 15-minute interval.

$$E_t \geq -250 \quad \forall t \quad (11)$$

Equation 12 states that photovoltaic generation in t is the efficiency times the installed capacity. The latter may be reduced by z_t segments (500 kW each) to meet Constraint (11).

$$PV_t = PV_t^{eff} \cdot (PV^{inst} - 0.5z_t) \cdot 0.25 \quad \forall t \quad (12)$$

$$z_t \in \{\mathbb{Z} \mid 0 \leq z_t \leq 2 PV^{inst}\} \quad \forall t \quad (13)$$

Peak loads are determined as below. The initial values $M_0^{peak}, M_0^{part}, M_0^{total}$ are provided by the supervising module and the respective demand maxima during periods before $t = 1$ that are in the same billing month.

$$M^{peak} = \max\left(0, M_0^{peak}, (E_1 \cdot 4 \cdot s_1), (E_2 \cdot 4 \cdot s_2), \dots, (E_{192} \cdot 4 \cdot s_{192})\right) \quad (14)$$

$$M^{part} = \max \left(0, M_0^{part}, (E_1 \cdot 4 \cdot r_1), (E_2 \cdot 4 \cdot r_2), \dots, (E_{192} \cdot 4 \cdot r_{192}) \right) \quad (15)$$

$$M^{total} = \max \left(0, M_0^{total}, (E_1 \cdot 4), (E_2 \cdot 4), \dots, (E_{192} \cdot 4) \right) \quad (16)$$

The schedule produced by the optimization module is implemented as is, which likely results in some sub-optimal decisions due to forecast errors. The only exception is that the battery is not charged if that would increase the current maximum demand, since the likelihood of such a decision being based on erroneous forecasts is very high. In the following evaluation, we will analyze whether the optimization module outperforms simpler decision strategies despite those forecast errors.

Evaluation Setting

While the optimization module requires data in 15-minute intervals, the historical data on photovoltaic generation at the base only contains hourly observations. The exception to this is a two week long test study in January 2013 that includes data in the appropriate intervals. These observations serve well to test the components and the overall system presented in this paper. At the time, only one megawatt of photovoltaic capacity was installed. However, we can easily scale this amount to reflect current and future situations, since it can be reasonably assumed that the generated power increases approximately linearly in the installed capacity. We split the datasets into two subsets. The first week is the training set that is used to estimate clear-sky generation for the first day of the second week, the test set. Once these days have passed, the observations are added to the training set to improve the forecast for future days, as explained earlier in this section.

Historical information on the cloud cover on those particular days is only available for every full hour and in qualitative form – categories, such as “clear”, “light rain”, “overcast”, or “haze”. We linked this qualitative information to the half hour before and after the respective full hour. For instance, if the reported condition is “clear” at 3 p.m. and “light rain” at 4 p.m., the intervals 2:30-2:45, 2:45-3:00, 3:00-3:15, and 3:15-3:30 would be labeled “clear”, with the following 4 intervals until 4:15-4:30 being labeled “light rain”. Naturally, this introduces a lot of uncertainty into the data, since it is unclear whether the reported condition prevailed for the entire hour. Also, qualitative data is by definition fuzzy. A label such as “overcast” can include a wide spectrum of situations, from a cloudy sky with occasional sunny spots to a sky filled with dark-gray clouds that suppress virtually all photovoltaic generation. However, the information system will eventually work with weather forecasts, which have their own inherent uncertainty. Nevertheless, it is likely that they are going to provide a more accurate prediction than the historical data we are working with for prototype testing due to two reasons. First, weather forecasts are quite accurate for 24-hour predictions and even 48 hours (although exponentially more unreliable after that). Second, weather forecasts include information on the actual cloud cover in percent, which provides much more accuracy than the qualitative information of the historical dataset. Hence, the results of our evaluation should be considered as lower bounds of the actual impact of the information system once it is implemented.

Evaluation Results

We will first evaluate the forecasting modules of the information system for the test week from 2013-01-25 to 2013-01-31. Afterwards, we will analyze the entire system, once for 3 megawatt-peak installed photovoltaic power (the situation when the system will be implemented) and once for 5 megawatt-peak.

Evaluation of the Load Forecaster

Since the load data is available in 15 minute intervals for several months, as opposed to the PV data, we could implement the load forecaster as explained earlier in this section. We forecasted the load for each day using a Fast Fourier Transformation of the load data for the three preceding days that share the same day-of-week. Holidays were counted as Sundays, regardless of their actual day-of-week (New Year’s Day and Martin-Luther-King-Day fell in our training set).

Table 2 suggests that the FFT-based forecasting works very well and confirms the visual comparison for a single day in Figure 5. The first column lists the average relative deviation over all 96 observations for each day (with the last row for the entire week). The deviation is calculated as $|(\hat{L}_t - L_t)/L_t|$, with \hat{L}_t and L_t as the forecasted and actual load values, respectively. The average deviation is consistently below ten percent

Table 2. Comparison of forecasted and actual loads (all values in percent)

	Average rel. deviation	Share with deviation < 10%	Deviation over entire period
Day 1	7.71	73.96	2.84
Day 2	8.23	83.33	2.89
Day 3	5.79	80.21	3.92
Day 4	6.36	86.46	1.34
Day 5	4.30	90.63	0.26
Day 6	3.48	95.83	0.53
Day 7	9.22	61.46	7.46
Week	6.44	81.70	0.61

for most days and for the week as a whole substantially so. This is enforced by the second column, which shows the share of observations with a deviation less than ten percent. With the exception of Day 7, this share is above 70%, indicating that the vast majority of estimates are almost spot on. When we consider the deviation over the entire period, i.e. between the forecast and actual values for the entire day / week, we can observe that these are very low, as well. It is especially noteworthy that the deviation over the entire week is almost zero. In summary, the load forecaster should serve our purpose quite well.

Evaluation of the PV Forecaster

Earlier in this section, we derived two regression models to forecast clear-sky photovoltaic generation. The first relates the natural logarithm of generation to the reciprocal of the sine of the sun altitude angle. While we do focus on clear-sky generation, the uncertainty introduced by the historical data on cloud cover still prevails, as illustrated in Figure 6. The light blue columns from 9:30 a.m. on January 29 to midnight on January 30 indicate that “clear sky” was reported for the entire interval. However, the generation curve for the first day is much more volatile, suggesting that clouds were still present that were not captured by the qualitative data. Since the forecast errors thus introduced into the regression model may be amplified in our logarithmic model, we derived a second model in Appendix A that relates photovoltaic generation directly to the sine of the sun altitude.

Similar to the load forecaster, we calculated the deviations between predicted and actual clear-sky generation to evaluate the models. The results are summarized in Table 3. Since photovoltaic generation exhibits a much higher coefficient of variation than load, we also considered the absolute deviations, in addition to the relative deviations. After all, for the optimization module a forecasted value of 500 for an

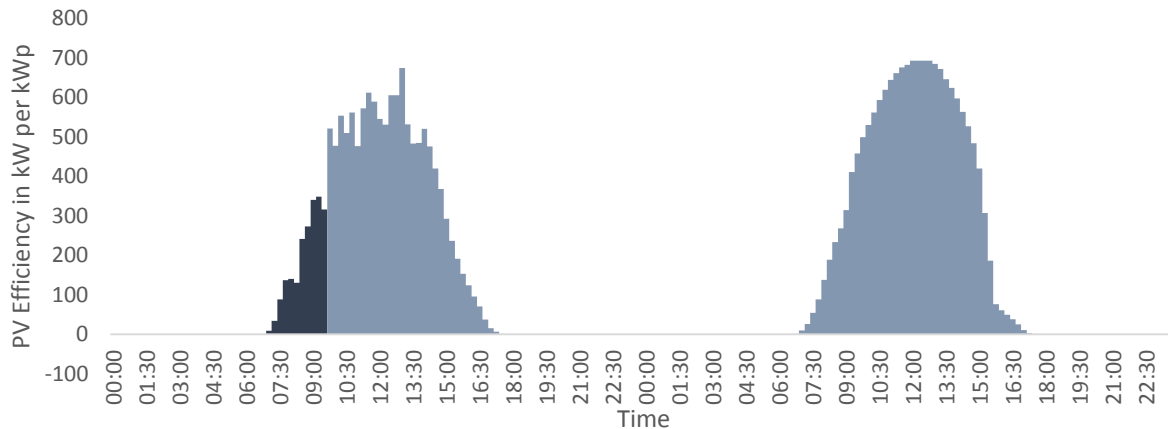


Figure 6. Actual PV efficiency for Jan 29 and Jan 30, 2013. Light blue columns indicate reported clear sky.

Table 3. Comparison of forecasted and actual PV generation (per MWp installed) for each model

	Model 1 (logarithmic)	Model 2 (linear)
Avg. absolute deviation (kW)	176.01	61.13
Avg. relative deviation (percent)	42.17	16.71
Mean Squared Error	57,701	7,400
Avg. relative deviation when actual PV > 600 kW (percent)	37.58	5.71

actual generation of 250 is much worse than a forecasted value of 40 given an actual generation of 20 – although the relative deviation is the same in both cases. Table 3 shows that the second, linear model substantially outperforms the logarithmic model. On average, the absolute deviations in the linear model are about a third as high as in the logarithmic model. This result is amplified when considering mean squared errors, where the linear model outperforms the logarithmic model by a factor of eight. While the relative deviation in the linear model is much higher than for the load forecaster, this was to be expected due to the uncertainty introduced by the qualitative data on cloud cover. Also, the fourth row shows that much of this uncertainty is caused by forecasts of low actual generation. Since the battery is likely needed during times of high generation – when the excess power exceeds the export limit – the second model produces very reliable results given the inherent uncertainty of the data for these times.

In summary, the forecast of photovoltaic generation is more difficult and less reliable than the load forecast. Nevertheless, given the uncertain qualitative data on cloud cover, the linear model provides quite accurate predictions, particularly for times of peak production which are the most relevant to battery management. Hence, we will employ the linear model in the evaluation of the entire system.

System Evaluation for 3 MWp installed

As there will be a photovoltaic installation with three megawatt peak power at the army base when the information system is implemented, we used this as the first case of our system evaluation. Recall the expectations for the information system we derived in the requirements analysis. We established that *forecast accuracy* is given, with both forecasters providing quite accurate predictions. The quality of the photovoltaic forecast should be a lower bound, since quantitative day-ahead weather forecasts are likely to be more precise than the qualitative historical data we work with. The *constraints*, such as battery and power export limitations, have been included in the optimization problem. This leaves *economic* and *ecological efficiency* as the requirements to be evaluated in this subsection. We compare the performance of our IT artifact to two benchmark cases. The first benchmark is a scenario without a battery as an energy buffer. The information system manages the battery charging strategies, so it is natural to compare it to this situation and assess the ecological effect of an IS-managed battery system. However, Brandt et al. (2013) have suggested that simple decision strategies for batteries may outperform optimization models when facing uncertainty. Their case study only considers a single household and electric vehicle, resulting in a much more volatile load and battery availability than in our case. Nevertheless, we choose such a simple decision strategy as our second benchmark to evaluate economic efficiency. According to this strategy, the battery always charges if excess PV generation exceeds the exportable amount, unless the battery is full. The battery is discharged if the load of the base exceeds PV generation.

Table 4. Results of system evaluation for 3 MWp installed

	Optimization	Decision Strategy	No Battery
Energy costs (USD)	10,031.89	10,028.29	10,070.32
Demand charge (USD)	13,850.73	14,977.48	14,977.48
Weighted sum (USD)	13494.57	13772.66	13814.69
Weighted sum (percent)	97.68	99.70	100.00
Disconnected PV segments	0	0	6

Table 4 summarizes the evaluation results and provides several interesting insights. First, for the 3 megawatt-peak installation in January, the battery is barely necessary if the focus is on ecological efficiency. During the course of the week, only six PV segments needed to be turned off because the export limit was exceeded. Naturally, the benefit of the simple decision strategy is very limited. The optimized schedule provided by our IT artifact on the other hand uses the battery to decrease demand charges even when the PV generation does not exceed the export limit. The reduction of those charges is quite substantial, with a drop of more than \$1,100. Since they are calculated on a monthly level and we only analyze one week, we weighted them accordingly to arrive at an overall drop of 2.32% in total energy costs. These first results confirm that a simple decision strategy is not suitable for the microgrid, since demand charges are only reduced if the times of highest demand and battery discharging randomly coincide. Since demand charges are a substantial part of total energy costs – even more so when PV output increases – the optimization approach is generally superior.

In the next step, we increase the installed power to five megawatt-peak. Thereby, we can get a better grasp of the ecological benefits when more panels are installed or during the summer months, when generation is generally higher.

System Evaluation for 5 MWp installed

When we consider an increase of installed PV power to five megawatt-peak – in the medium run even an increase to eight is planned – the ecological benefits of the IS-controlled battery system become more evident. The results in Table 5 illustrate that the number of PV segments that need to be disconnected is reduced by 78, or 22 percent. Over the course of the week the additional energy that could be generated this way added up to six megawatt-hours or an increase of 5.4% compared to the situation without batteries.

Also in this case the maximum demand charge is still substantially reduced. However, the information system now also uses excess photovoltaic generation to drive down energy costs. Overall, weekly energy costs are reduced by \$700 or six percent.

Discussion

In this section we first discuss the technical and economic implications of our work. This is followed by suggestions on the future role of Information Systems research with regard to Microgrids and Smart Power Systems.

Technical and Economic Implications

The evaluation in the previous section illustrates that the information system we designed contributes both to the economic and ecological efficiency of the microgrid. Despite the inherent uncertainty of forecasted load and PV generation, the information system allowed for an additional six megawatt-hours of photovoltaic energy to be generated over the course of the week. Consider that the minimum charge of the battery is 20 percent, charging efficiency is 0.92, and on a typical day the battery successively charges during the morning and afternoon, and discharges in the evening. The resulting theoretical maximum of additional PV energy over the week is around 6.6 megawatt-hours. Hence, the ecological efficiency of our system is very close to the theoretical maximum, especially when considering that first day in our sample was very cloudy.

Table 5. Results of system evaluation for 5 MWp installed

	Optimization	No Battery
Energy costs (USD)	7,344.23	7,799.55
Demand charge (USD)	13,769.61	14,731.52
Weighted sum (USD)	10,786.64	11,482.43
Weighted sum (percent)	93.94	100.00
Disconnected PV segments	280	358

While not the primary focus of the project, it is interesting to consider the economic implications of our results. Our information system uses the battery not only to store excess photovoltaic power, such as a comparable trigger strategy would do as shown above, but also to actively keep demand charges down. We only analyzed a sample week in January, but we can use these results as a lower bound for the entire year. Cost savings are likely higher during the summer, since prices for energy and demand are higher, and the number of sunny days increases.

As Stadler et al. (2013) point out, stationary battery technology is still too expensive for the costs to be recovered. Consequently, we first analyze how much our information system contributes to cost recovery given current technologies. While the costs for the actual battery at the base cannot be disclosed, PG&E recently launched a battery storage system with four megawatts of power at \$3.3 million (Kligman, 2013). Hence, the current costs of a system similar to the one we considered (1.25 MW) should be around \$1 million. The lifespan of the PG&E system is about 15 years. If we consider the weekly savings of the 5 MWp scenario at \$700 to be representative of the year (as discussed above, it is more likely to be a lower bound) and a discount rate of five percent, about 41% of investment costs are recovered during the lifetime of the battery.

However, utility-scale battery technology is rapidly evolving. The company EOS Energy Storage intends to launch a zinc-air based battery by 2015 at a price of \$200 to \$250 per kWh (Parkinson, 2013) and a lifespan of up to 30 years. Even assuming battery costs of \$300 per kWh and annual operational costs of \$10,000 (e.g. for IS operation), investment costs would be recovered after 15 years – half the lifespan of the battery. As we considered a lower bound for energy savings, the actual break-even point may arrive even sooner.

Environmental sustainability in itself is an important goal for our society and in this paper we show from a technical perspective how information systems can contribute to that goal by increasing the efficiency of renewable energy systems. However, the examples discussed in this section also show that they increase the economic feasibility of these solutions. With the rapid technological advancement of utility-scale batteries, information systems, such as the one we designed in this paper, will be necessary to enable the full potential of microgrids. Thereby, they make the investment in sustainable energy technologies not only the ecological but also the economic thing to do.

Implications for IS Research

While this work focusses to a substantial degree on the technical aspects of implementing an information system in a Microgrid context, we must also acknowledge the possible contribution of IS research with respect to the socio-economic environment of a future power system. After all, this technical focus has only been feasible because the agendas of the stakeholders in our case study were quite straightforward and aligned with each other. As discussed earlier, the primary goal of the U.S. government as operator of the base is to increase the ecological efficiency of the photovoltaic system installed there. Due to the experimental and showcase nature of the project, economic considerations are not as binding as they may be in other situations. The utility company as the second stakeholder in the system seeks to reduce the variance of photovoltaic power fed into the grid by the base. However, this objective is neatly codified in the power export limit of one megawatt. The base itself follows strict schedules and clear hierarchies. Altogether, this study is very close to the *ideal case* to assess the technical benefits of an energy information system.

The necessity of future IS research is emphasized once this environment becomes more complicated and complex, as for microgrids in large office buildings or residential neighborhoods. The number and heterogeneity of stakeholders substantially increases and economic considerations become a decisive factor. For instance, in the case of a residential microgrid, households with photovoltaic panels and other forms of energy generation may have different objectives than households without these devices. The distribution of costs and benefits of the microgrid must provide sufficient incentives to participate to all agents. Once this social aspect is taken into consideration, there are several streams in IS research that may provide valuable contributions in the future.

- **Service Research.** As illustrated by the power export limit in our case study, the agendas of the stakeholders must be codified in some contractual form. The benefit of a household to shift demand in a manner beneficial to the overall microgrid must be clearly stated. This gives rise to a variety of new energy services (Strueker and van Dinther, 2012) which can build upon established research on IT services.

- **Privacy Research.** In our case study the operators of the microgrid, of the PV installation, and of all demand loads were the same entity. Once this changes, privacy issues become a valid concern, as agents may not be as willing to share all information necessary for an optimal operation of the microgrid.
- **Human-Computer Interaction.** The army base in our case study followed to a substantial extent strict, centrally organized schedules. On the contrary, a microgrid of residential households needs to take into account and affect the behavior of many heterogeneous agents. This requires more interaction between the “smart” microgrid and the users. IS research can provide insights on interfaces, designs, and strategies for this interaction, as exemplified by the Velix energy management system in Loock et al. (2013).

Conclusion

On the path towards an environmentally sustainable energy supply, microgrids are considered to be a key technology. They enable the integration of distributed renewable energy sources and increase the robustness of the overall power system. However, an efficient coordination of the microgrid requires information about future supply and demand, and needs to incorporate organizational, contractual, and physical constraints. Research on the corresponding information systems is mandatory to successfully overcome this challenge.

The goal of this paper was to develop and evaluate a prototype of such an information system, so that it can eventually be implemented as part of a pilot study in a U.S. military base. More specifically, our research questions related to the requirements the information systems needs to meet, the actual information system design, and whether the resulting IT artifact satisfies those requirements. Based on the project setting and the agendas of the project stakeholders, we determined that the IT artifact must improve the ecological efficiency of the system by reducing the number of incidents when parts of the photovoltaic installation need to be disconnected. Furthermore, it needs to be able to forecast uncertain information on load and generation sufficiently accurately and incorporate organizational and physical constraints. Finally, it needs to reduce the overall costs of the battery system compared to less sophisticated management strategies.

The IT artifact we designed consists of several modules, including two for forecasting (load and photovoltaic generation), one for optimization, and one supervising module. While the constraints were incorporated into the optimization problem, our evaluation showed that the other requirements are fulfilled, as well. Both forecasting modules exhibit low prediction errors, with the error of PV forecasts being slightly higher due to qualitative weather data. We could also show that our information system is able to directly target and reduce demand charges, making it economically superior to simple trigger strategies.

Most importantly, the primary goal of ecological efficiency is achieved. Over the course of our test week, the system enabled the generation of six megawatt-hours of additional clean photovoltaic energy. We could show that for a typical week with the battery charging during the day and discharging in the evening, this is very close to the theoretical maximum.

The evaluation also illustrated that with improving technology and falling battery prices, investments in energy storage may soon turn out to be not just the best decision from an ecological, but also an economic perspective. We estimated that even in a worst-case scenario, battery prices of \$300 per kWh can be recovered well before the end of the lifespan of the battery, including operational costs. Hence, the implications of our results go beyond this pilot study. We could demonstrate the improvements in ecological and economic efficiency large building complexes can achieve through IS-supported microgrids. Given the anticipated reductions in prices of energy storage, this provides a viable model for government facilities, but also large office buildings.

Naturally, the next step for our research is to implement the information system at the base. Given the positive assessment of the prototype despite very conservative assumptions, we will evaluate the system to determine its ecological and financial potential over the course of the year. This should provide an even better understanding of how IS research can aid public institutions in reducing their environmental footprint and promoting sustainability.

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Appendix A

Derivation of Model 2 for the PV forecasting module:

Recall Equation 2:

$$P_t^{PV} \sim A e^{-\frac{k}{\sin \beta_t}}$$

In the interval [0.05, 0.975] (we set expected generation to zero for angles less than 0.05, since it is either night or early dawn / late dusk) we can approximate $\ln(\sin \beta_t)$ reasonable well as $-p/\sin \beta_t + q$, with p and q as some constants, particularly with $p \sim 0.18$. This yields

$$P_t^{PV} \sim A e^{\frac{k}{p} \ln(\sin \beta_t) + \frac{kq}{p}}$$

which in turn translates to

$$P_t^{PV} \sim A (\sin \beta_t)^{\frac{k}{p}} + z$$

with $z = A e^{\frac{kq}{p}}$. As Masters (2004) points out, k varies between 0.142 and 0.207. With $p \sim 0.18$, the exponent is very close to 1 (given the short term relevance of our model, we can even set $p = k$ and still find a q that provides a good approximation), such that:

$$P_t^{PV} \sim z + A \sin \beta_t$$

This relationship can be estimated through a linear model. A similar result can be reached through a Taylor Expansion of the right-hand side of Equation 2.

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